Activities of Daily Living Ontology for Ubiquitous Systems

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Abstract— **Ubiquitous eHealth systems based on sensor technologies are seen as key enablers in the effort to reduce the financial impact of an ageing society. At the heart of such systems sit activity recognition algorithms, which need sensor data to reason over and a 'ground truth' of adequate quality – used for training and validation purposes. The large set up costs of such research projects and their complexity limit rapid developments in this area. Therefore, information sharing and reuse, especially in the context of collected datasets, is key in overcoming these barriers. One approach which facilitates this process by reducing ambiguity is the use of ontologies. This paper presents a hierarchical ontology for activities of daily living (ADL), together with two use cases of 'ground truth' acquisition in which this ontology has been successfully utilised. Furthermore, these studies are reflected upon from the machine learning perspective, and the use of this ontology in clinical studies is discussed.**

I. Introduction & Background

Healthcare needs have changed dramatically in recent times. An ageing population and the increase in chronic illnesses, such as diabetes, obesity, cardiovascular and neurological conditions, have influenced research, directing it towards Information Communication and Technology (ICT) solutions. These technologies make up ubiquitous systems, which quietly reside in the background and gather relevant, actionable information from various sources – mainly sensors. Something that was envisioned by Mark Weiser back in 1991 [1] is now becoming a reality. Such systems are developed and used in the context of Ambient Intelligent (AmI) spaces, Ambient Assisted Living (AAL) and wearable healthcare systems – to name a few.

A large part of our lives, increasingly so as we grow older, is spent in the home, yet very little is known about our activities and behaviour in the home. Learning about the Activities of Daily Living (ADL) of people living in AAL spaces is key to answering many clinical questions, such as the cause and effect of various medical conditions or the effectiveness of various treatments and interventions. Efficient and accurate activity recognition (AR) algorithms are needed in order to make sense of this data and provide useful/actionable information and services in the human activity monitoring context. Such an algorithm must produce machine-understandable data so that the data can be linked across many different domains. The same applies to 'ground truth' acquisition mechanisms, which aim to facilitate the development of AR algorithms by providing useful and interoperable activity labels. One way to facilitate this is to use formal information structures, such as ontologies. In this way the ambiguity of labels is reduced. The use of common models facilitates cross-discipline collaboration, knowledge exchange and reuse.

SPHERE is one example where the use of ontologies is beneficial. Sphere is a multi million project consisting of large number of researchers with the work distributed across multiple work packages across multiple universities. One group is responsible for the development of AR algorithms, another group for developing mechanisms for acquiring 'ground truth' and another for collecting data. All these groups must communicate and collaborate with each other as well as with other stakeholders. For this purpose the SPHERE ADL ontology was developed, and is now widely used across the project.

There are few projects developing taxonomies or ontologies covering activities of daily living. One such is BoxLab – a project in the US funded by National Science Foundation, whose mission is to make home activity datasets a shared resource. On their website one can find the activity taxonomy available to download[1] in an XML format. Definitions of all labels are also available. BoxLab captures a large number of classes and each ACTIVITY has the following properties: social context, activity and room location. To the best of our knowledge no formal model of this ontology has been published in the literature. Another example is the Compendium of Physical Activities (CPA) – project supported by Arizona State University and National Cancer Institute in US. On their website[2] they list 21 activity categories currently included in the CPA. Home Activity category lists activities with corresponding codes. These activities are not organised hierarchically but rather make up a flat list that contains information which could be though of as parameters of these activities. For example, 'cleaning, sweeping carpet or floors, general', 'cleaning, sweeping, slow, light effort' and 'cleaning, sweeping, slow, moderate effort' are three different activities. In fact, these can be though of as one activity with different parameters, e.g. the effort level. At the same time the first activity in this list is very ambiguous as it ends with the word 'general'. What is its relationship to the other two cleaning/sweeping activities?

The remainder of this paper introduces the SPHERE ontology of activities of daily living in detail. It also demonstrates the use of this ontology in two use cases. The first of these use cases consists of a post-hoc observer annotation of scripted

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[1] http://boxlab.wikispaces.com/Activity+Labels

[2] https://sites.google.com/site/compendiumofphysicalactivities/Activity-Categories/home-activity

experiments and the second is an unscripted self-annotation in free living. These studies are reflected upon from a machine learning perspective. We then provide a brief introduction to our current work, which explores the use of SPHERE ADL ontology in the context of clinical studies. This paper then concludes with Discussions and Future Work.

II. Ontology for Activities of Daily Living

The SPHERE ontology for activities of daily living lists and categorises activities occurring in the home environment. No model is fully complete, hence this ontology is expected to evolve over time. The initial dictionary of ADLs was compiled during project meetings between researchers from the SPHERE project and clinicians (and is reported on in this publication [2]). The result of this collaborative effort has been extended for completeness (by which is meant adequacy of coverage sufficient to respond to all defined competency questions [3]) mainly with activities found in the Compendium of Physical Activities[2]. The final stage involved merging it with BoxLab's taxonomy[1]. Compliance with existing models ensures interoperability and applicability of collected datasets beyond the project.

In-line with BoxLab's model, ACTIVITY has the following properties: *activity, physical state* (posture/ambulation in BoxLab's model), *social context* and *room location*. Furthermore, as represented by Fig. 1, the ontology has been extended with additional properties, namely *physiological context, (at) time, (involve) object, (involvedAgent) person, ID,* and *sub-activity* with a self referencing relation. Thus, each activity occurs at a certain point in time, is identifiable by some unique ID. Moreover it can involve physical object(s), people and might be made up of a number of *sub-activities*. Physiological context/signals are also of importance due to application of this ontology for healthcare and monitoring people living independently in the safety of their own homes. Overall, AAL technologies have to ensure user's safety and monitoring physiological signs is one way to deliver it. The market of wearable sensors and smart-phones reflects this interest, as more products offer, for example, heart rate monitoring features. Fig. 2 depicts the structure and class definitions of the SPHERE ontology for ADL, the latest version of which, in the OBO[3] format, is available from the data.bris repository (DOI: 10.5523/bris.1234ym4ulx3r11i2z5b13g93n7).

Structurally speaking, BoxLab's model could be viewed as two-tiered taxonomies of labelled concepts, separated into general categories and specific subcategories. The SPHERE ADL ontology originates in a similar hierarchy of concepts, developed following Noy's methodology[3] with reference to BoxLab's work, and tested using competency questions developed within SPHERE. This was then expressed in OBO, since an assessment of the proposed domain of use indicated that this standard dominated in the biomedical domain.

A. Activity Hierarchy

In the SPHERE ADL ontology, ADL are organised hierarchically. *Activity* has 20 sub-classes out of which 15 are present (albeit some names may differ slightly to better reflect classes listed in the subclasses below) in the BoxLab taxonomy. These changes are listed in Table I. Five new categories were added to capture additional ADL and to reflect aspects related to health. These include *atomic home activities, health condition, social interaction, working*, and *miscellaneous* (shortened to 'misc').

TABLE I
New and altered *activity* subclasses.

Activity Subclasses	
BoxLab	SPHERE ADL Ontology
Eating	Eating/drinking
Home management	Home environment management
Information	Information interaction
Meal preparation	Meal/drink preparation
—	Atomic home activities
—	Health condition
—	Misc
—	Social interaction
—	Working

Activities often involve interactions with one or more object. These interactions/activities have been reflected in the ontology in the *Atomic home activities* class and its subclasses. These capture the low-level activities or simple actions which form the basic building blocks for other activities (evidencing sub-activities). One can use these labels to identify short actions for use in AR algorithms. With the increasing sophistication of wearable technology and sensing, research into identifying these types of activities will become more prominent. In the current version of the ontology, *Atomic home activities* has the following subclasses: *door interaction, window interaction, object interaction, tap interaction, cupboard interaction, draw interaction*, and *electrical appliance interaction*, each with a further level of subclasses (omitted for brevity).

The *Health condition* class is essential to describe activities and behaviours in the context of a person's health. By training algorithms for AmI or AAL applications and associating level of participation in activities and incidence of symptoms with a person's well-being, early warning signs that someone is unwell or in need of assistance or medical treatment could be predicted. This is especially important given the health challenges currently facing society and their inherent socioeconomic impact. This category currently includes: *coughing, fall, fever/infection, shaking* and *sweating*.

Social interaction is comprised of: *receive visitors, social media, talking* (with subclasses), and *video calling* activities. Finally, *working* is further divided into *intellectual* and *physical work*. Every subclass of *activity* (listed in Table II) has a *misc* member to enable annotation of knowledge which the ontology does not explicitly capture. *Misc*, in Table I, is for activity labels which do not fit into any of the existing classes and currently has *smoking tobacco*.

[3]http://oboedit.org/

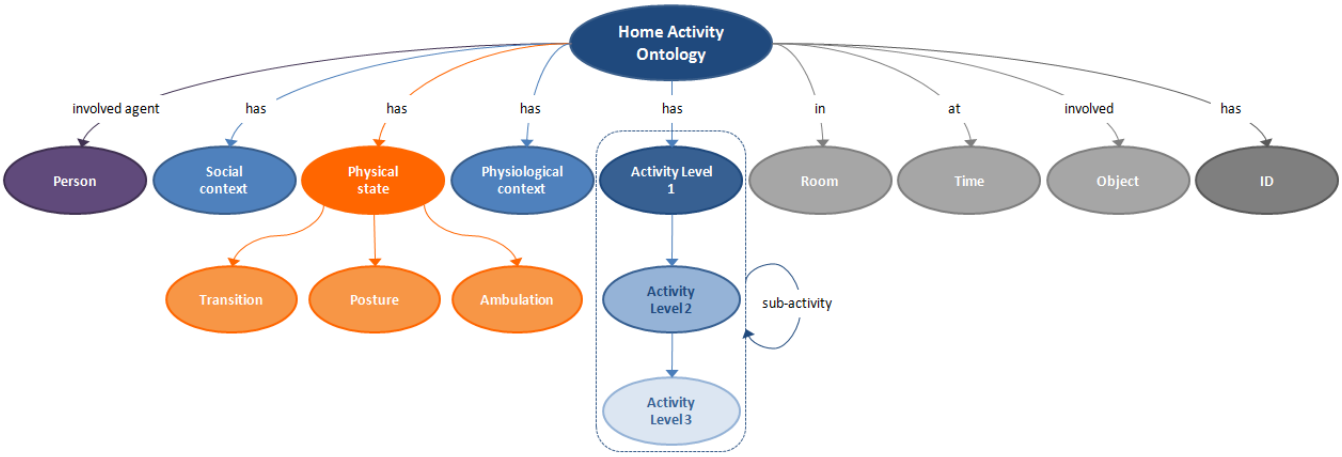

Fig. 1. High-level view of ADL ontology.

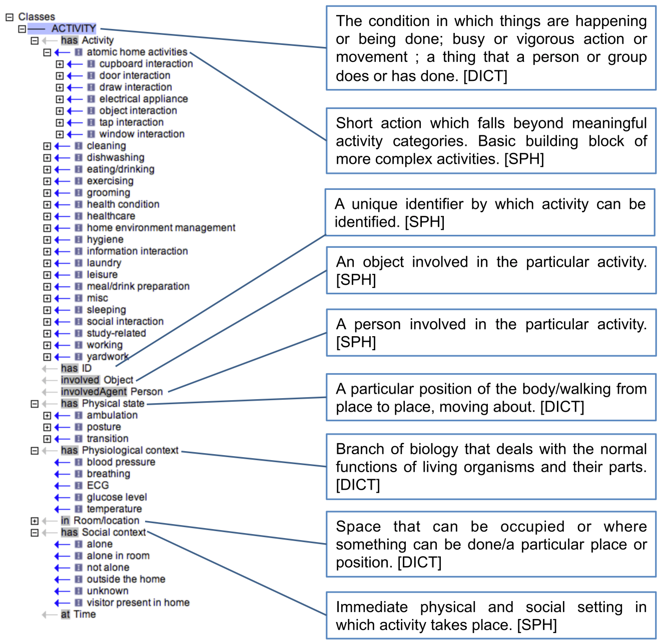

Fig. 2. High-level overview of the entire ontology.

B. Ambulation, Postures, and Transitions

The structure of *Physical state* directly reflects BoxLab's ontology *posture/ambulation* category, yet has been extended with additional entities. It has three subclasses, namely *ambulation, posture*, and *transition*. Table III provides the hierarchy of *Physical state* classes listing the number of subclasses and examples for each. Since activities do not always describe a person's posture (with some exceptions, e.g. *running* where the posture is inherent in the activity), it is important to capture this information separately.

C. Contextual Information

Room/location, social context and physiological context make up contextual information. For any activity it is beneficial to know the context in which it occurred. Some activities are associated with a particular location (bathing activity in bathroom location) where some can occur anywhere inside or outside the home environment. From the healthcare point of view, it is also important to capture social context as people's behaviour can be affected by presence of other individuals. Finally, physiological context such as blood pressure or glucose level have influence on our well-being and behaviour. Information captured without context is of limited value as it does not fully reflect reality. Classes and examples of the three contextual information categories described above are provided in Table IV. In addition, activities consist of *(involved) object* and *(involvedAgent) person* properties, which capture object(s) and people involved in a particular activity. Since some activities can be made up of shorter (in duration) activities, *sub-activity* relation was introduced. For completeness, (has) ID attribute was introduced to differentiate between activities. All these properties and relations are captured in Fig. 1

III. Case Studies in Use of the SPHERE ADL Ontology

Since the initial release of the SPHERE ADL Ontology, it has been used in a number of operational contexts both within and external to the SPHERE project. In this discussion, we discuss several of these use cases.

We begin with the most straightforward of these, the use of the ontology within an annotation tool used by a post-hoc observer working from scripted, recorded data (in this case, video data) [4]. The second case is the use of the ontology within an annotation tool [5] intended to support unscripted annotation in free living within a 'smart' home environment, in this case a home in which the SPHERE system is deployed.

A. Post-hoc (retrospective) observer annotation of scripted experiments

The development of ambient assisted living systems frequently mandates collection of 'ground truth' annotations.

TABLE II

ACTIVITY CLASSES IN THE SPHERE ADL ONTOLOGY, INCLUDING THE HIGHEST AND SECOND HIGHEST ONTOLOGY LEVELS AND THE NUMBER OF SUBCLASSES IN EACH CLASS.

Class	Subclasses	Example
Atomic home activities	7	
door interaction	3	open door
object interaction	6	pick up object
tap interaction	6	open hot tap
window interaction	2	close window
electrical appliance	4	switch on
cupboard interaction	2	open cupboard
draw interaction	2	open draw
Cleaning	17	mopping
Dishwashing	8	drying dishes
Eating/drinking	5	eating a meal
Exercising	6	stretching
Grooming	9	shaving
Health condition	6	coughing
Healthcare	3	treating a wound
Home env. management	9	water plants
adjusting light levels	2	switch light on
Hygiene	9	flossing
Information interaction	10	writing
using a computer	3	email
using a mobile phone/pda/...	4	sms
Laundry	11	ironing
Leisure	11	dancing
Meal/drink preparation	9	preparing a snack
Misc	1	smoking tobacco
Sleeping	5	napping
Social interaction	5	social media
talking	4	on a phone
Study-related	4	putting on sensors
Working	3	intellectual
Yardwork	3	gardening

TABLE III

PHYSICAL STATE CLASSES IN SPHERE ADL ONTOLOGY.

Class	Subclasses	Example
Ambulation	9	crawling
Posture	7	kneeling
sitting	2	sitting on the floor
standing	2	standing still
Transitions	13	bending

These are primarily used to support the training and testing of models able to provide reliable predictions of aspects of human activity.

Whilst the ultimate goal is to enable reliable prediction in free-living contexts (i.e. identifying unscripted activities in as naturalistic a dataset as possible), the practicalities of system development mean that this is ordinarily a multi-stage process. We began with a series of scripted activities, noting that each of the activities selected could be represented using the SPHERE ADL ontology – had this proven not to be the case, it would imply either that the task was out of scope for the ontology, which we did not believe to be the case, or that the ontology required further refinement.

Video data was collected during each scripted experiment, using a head-mounted video camera. This data was then annotated. Initially, the ANVIL tool was used for this purpose [6]. However, the team subsequently adopted the ELAN annotation tool, developed by MPI Nijmegen [7] for the purpose of creating complex annotations on video/audio resources[4]. ELAN, initially designed to permit annotation with arbitrary vocabulary, has been extended for ontology-based annotation [6]; this functionality can also be effectively simulated by mandating the use of a controlled vocabulary for a given 'tier' (annotation layer).

TABLE IV

ROOM/LOCATION, SOCIAL CONTEXT AND PHYSIOLOGICAL CONTEXT CLASSES IN SPHERE ADL ONTOLOGY.

Class	Subclasses	Example
Room/location	16	loft/attic
Social context	6	not alone
Physiological context	5	glucose level

ELAN is based around the concept of annotation of a timeline, and therefore, of events with a non-negligible duration. There is a possibility that imposition of constraints can avoid invalid descriptions, such as an individual being reported to appear in two rooms simultaneously, which are reported to occur in similar place-based annotation datasets [8]. At present, this is left to the interface. The potential for temporal representation and reasoning within the ontology itself remains, although there is limited support within OBO for automated reasoning and validation (discussed below).

B. *Unscripted self-annotation in free living*

Annotation in free-living is a significant component in the validation of potential solutions for AAL, despite the attendant complexities. Several factors complicate self-directed annotation, such as the complexity of any available interface and the inherently problematical nature of any means of documenting an activity that inherently requires that activity to be put on hold.

For the purposes of SPHERE, an in-house application was developed for the Android operating system that allows for flexible, time-based annotation using terms selected from the SPHERE ontology of ADLs. This was provided to study participants in the SPHERE project who elected to stay in the initial SPHERE pilot install home, a two-storey building near the University with a well-tested and effective sensor network home installation. This application supported a variety of interaction modes including voice input (via a speech-to-text service), menu navigation and RFID/NFC 'tap' functionality. An initial review of the outcomes from this study is available [5].

C. *Data post-processsing for machine learning systems development*

In technology research, it is commonplace to make use of agile development methods when scheduling and specifying work, focusing on requirements currently expressed by stakeholders. The result is often to create products that are 'sufficient unto the day' – able to support development of a

[4]https://tla.mpi.nl/tools/tla-tools/elan/

solution to the immediate problem, but potentially inflexible and of limited broader application. However, in large studies, the costs, complexity and logistics of data collection and preprocessing are considerable. The process of annotation itself is a significant investment, irrespective of the complexity of the specific annotation schema selected for use. There are sound reasons to make use of a highly-structured approach to information annotation; although this increases costs relative to a simpler schema, it remains significantly cheaper than re-annotating a data set *in toto*.

Where supervised machine learning methods are used, classifier development for a given purpose generally requires a specific, concise 'ground truth' tailored to that purpose. Given a set of annotations drawn from a well-structured, multi-tier ontology, it is straightforward to generate a simplified graph from a full timeline of annotations, fulfilling the functional requirements of the task. For example, an annotation set suitable for evaluating a location classification algorithm can be generated by filtering all annotations other than location from the graph. Similarly, selecting all annotations in the *hasPhysicalState* branch results in an annotation set suitable for exploring classifiers of physical motion – for example, developing a *sit to stand* transition classifier or timer.

D. Preparing for clinical studies

SPHERE systems used as AAL sensor networks are expected to operate as a proxy for traditional instruments used in healthcare, such as clinical outcome measures, which are used to document and evaluate patient state and progress. With this in mind, clinicians were extensively involved in the initial development phases of the SPHERE ADL ontology. Data collection is now underway in the initial SPHERE studies, including the 'Hundred Homes' study, in which the system is deployed in a wide variety of homes around Bristol. Several healthcare-focused studies associated with SPHERE have also begun, focusing on specific clinical conditions such as dementia and recovery from surgery such as hip and knee replacement.

The process of mapping relevant clinically related instruments (i.e. bases for measurement of patient condition) and outcome measures to the ADL ontology is now ongoing. To achieve this, it is useful to represent these clinical information structures as ontologies in their own right, mapping between them to establish correspondence or more complex relations or reasoning. These ongoing studies provide a useful opportunity to 'stress-test' the SPHERE ADL ontology, evaluating whether it is expressive enough to fully support the contexts in which it is used.

E. Superfluity and simplicity of use

In conclusion to this section, we take a moment to consider the limitations of the SPHERE ADL ontology as it is presently expressed. The SPHERE ADL ontology is built using Open Biomedical Ontologies (OBO) tools and standards [9]. OBO is a relatively informal approach to the development of hierarchical concept representations, built in parallel to OWL (Web Ontology Language) [10] and intended for use within the biomedical sciences. We have already touched on one such limitation – limited support for automated reasoning/ validation. Consider the example of a potentially superfluous concept: the ontology explicitly defines both *alone* and *not alone*. As with most information structures of significant scale, the SPHERE ADL ontology contains a number of potentially superfluous concepts [11]. This specific example breaks the principle of orthogonality [12], since the two terms are closely coupled. One might reasonably ask why both are required, since negating the first implies the other.

1) Annotating an open world: In ontology design, particularly in the theoretical underpinnings of OWL, the open-world assumption (partial knowledge of the world) is made – i.e. what we do not know, we cannot guess at one way or another. It is not valid to make the assumption that, for example, any individual whose social context is not specifically defined must be 'alone'. This echoes our experience of the ways in which the SPHERE ADL ontology is used. Pragmatically, most uses of the SPHERE ADL ontology are not exhaustive – rather, they are partial annotations, making use of a task-relevant subset of the ontology. Despite the benefits of rich annotation, even a post-hoc annotator is unlikely to annotate exhaustively. Participant-driven annotations are even less likely to provide a complete view.

With this in mind, recording the *provenance* of contributed annotations is a useful precaution to take in order that the origin of any given annotation can always be ascertained [8]. For now, this is managed organisationally, although several popular methods allow direct integration into the ontology.

2) OBO, OWL and heterogeneous infrastructure: In a pure OWL environment, it is possible to use automated reasoning to restrict and constrain values. For example, we might encode *isAlone* as, for example, isAlone has Value exactly $1\{y,n\}$ where $y \neq n$ – that is, a subject may either be alone or not alone, but cannot be both simultaneously. The ADL ontology does not presently permit automated validation to avoid such inconsistencies – such validation must occur *post hoc*.

OBO does not focus on automated reasoning, unlike OWL, and its ability to express relations between concepts is limited. However, it is much more convenient for use in the biomedical sciences due to the popularity of the language and tools. The practicality of direct implementation of automated validation using OWL or its more powerful cousin SWRL [13] is limited by the fact that many tools used in SPHERE do not directly support OWL or OBO, requiring instead a lossy transform into a simpler controlled vocabulary. As support for these standards continues to develop, an OBO-to-OWL mapping can be used on both ontology and instance data in order to enable their usage.

IV. Discussion and Future Work

This paper presents the SPHERE ontology of ADLs, two completed use cases and two ongoing use cases – machine learning and support for clinical studies. Ontology is a specification of a conceptualisation, i.e. it defines classes, their attributes and relationships between them in a particular domain of interest. Therefore it might be difficult to understand and use by users outside of the specific domain. AAL is one area of research which benefits vastly from the use of a common, well-defined model. Such an approach eliminates any ambiguities and enables machines to reason over data; it also facilitates enables interdisciplinary, future-proof research. Ubiquitous systems are often linked to the Internet and contribute a large amount of data which is reasoned over not only by machines but also by stakeholders with different expertise.

The first use case presented in this paper demonstrates how the SPHERE ontology of ADLs was used to annotate video 'ground truth' data. Three tiers were assigned to describe activities in terms of detail from high level activities to low level activities. Therefore, such 'ground truth' is usable for validation of AR algorithms inferring activities at any of the three levels of granularity. Performing such video annotations required some in-depth knowledge of the ADL domain and hence annotators were briefed and trained to understand the modelled concept. Details of this study can be found in [4].

The second use case exposed the ontology to non-expert, untrained users facing the task of self-annotation of ADLs. Participants could log their activity via speech, NFC and through the use of buttons carrying activity labels, organised by room/location – more in [5]. Participants with no prior knowledge who faced this task had no problems understanding or using the provided tool. Hiding the complexity of the ontology in various software tools is very important. Otherwise untrained, non-expert users may find such tools difficult to understand and impossible to use intuitively.

Other than these two case studies, the SPHERE ontology of ADLs is to be used in clinical studies. SPHERE is a sensor platform for healthcare in residential environments and hence clinicians are interested in monitoring specific ADLs and behaviours. There is an ongoing need to map between the activities and states presented in this ontology and the conceptual graphs in use by clinicians – for example, an occupational therapist may evaluate a patient's ability to complete variety of ADLs as outcome measures, including activities as straightforward as making a cup of tea [14].

Future work includes mapping free speech to ontology terms, which involves extending this ontology with synonyms or linking to online dictionary services or linked data resources such as OntoWordNet. Interface design surrounding ontologies often falls prey to the so-called 'pathetic fallacy of RDF' [15] – the expectation that, because the underlying information structure has a certain form, in this instance a graph with concept labels, the resulting interface should display this directly. In practice, a concept synonym could be presented in the form of an utterance, a gesture, haptic interaction or an RFID activation, and the user may never view the ontology directly.

V. Conclusion

Observation of the SPHERE ADL ontology in use has allowed us to identify strengths and weaknesses, as well as opportunities to develop the structure further. Work continues on alternative forms of data input, mapping and evaluation. For the purposes of automated reasoning and validation, we are exploring the possibility of making fuller use of existing mappings between OBO and OWL, opening up the potential for use of a wider variety of validation, constraint and mapping tools designed by the Semantic Web community. Our work remains guided by practicality, alongside data quality metrics and concerns.

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